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COMPRESSIVE SENSING BY COLPITTS CHAOTIC OSCILLATOR FOR IMAGE SENSORS

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Abstract- Compressive sensing uses simultaneous sensing and compression to provide an efficient image acquisition technique and it has been demonstrated in optical and electrical image sensors. To guarantee exact recovery from sparse measurements, specific sensing matrix, which satisfies the Restricted Isometry Property (RIP), should be well chosen. Toeplitz-structured chaotic sensing matrix constructed by Logistic map has been proved to satisfy RIP with high probability. In this paper, we propose that chaotic sequence sampled from Colpitts oscillator can also be used to generate Toeplitz-structured chaotic sensing matrix. Simulation results show that the proposed Colpitts chaotic sensing matrix has similar performance to random matrix or other chaotic matrix for exact reconstructing compressible signals and images from fewer measurements.

Index terms*:* Compressive sensing, image sensors, chaos, Colpitts oscillator.

I. INTRODUCTION

Image sensors are of increasing importance in applications such as biomedical imaging, sensor networks [1, 2], hand-held digital cameras [3] and so on. Nowadays image sensors are under increasing pressure to accommodate ever lager and higher dimensional set; ever faster capture, sampling and processing rates; ever lower power consumption; communication over ever more difficult channels; and radically new sensing modalities. Fortunately, a new sampling theory, compressive sensing (CS)[4-6] is proposed and demonstrated in optical and electrical image sensors[7-11], which can reduce the number of the sensors and faster the image acquisition time. The basic idea of CS theory is that when the signal is very sparse or highly compressible in some basis (i.e., most basis coefficients are small or zero-valued), far fewer measurements suffice to exactly reconstruct the signal than needed by Nyquist-Shannon theory. In CS, instead of sensing the entire image and then subsequently removing redundant information during the compression step, sensing and compression are combined as one process and only the required or non-redundant information is sensed, that is, a number of random projections of the image are being sensed as the compressed version of the image. This principle of “sample less, compute later” shifts the technological burden from the sensor to the processing.

The two fundamental questions in compressed sensing are: how to construct suitable sensing matrices, and how to recover the signal from a small number of linear measurements efficiently. Here we lay emphasis on the first problem. According to the CS theory, measurements of the image are taken using the measurement matrix (or the sensing matrix), which should satisfies the so-called Restricted Isometry Property (RIP), that is, the measurement matrix is supposed to be incoherent with the matrix describing the sparse basis. Recent Studies show that feasible, judicious selection of the type of the measurement matrix may dramatically improve the ability to extract high-quality images from a limited number of measurements and may reduce the hardware complexity in design [12]. In theory, the optimal incoherence is achieved by completely random measurement matrices, such as Gaussian, uniform, Bernoulli and so on [13-15]. However, such matrices are often difficult and costly to implement in hardware realizations. Since chaotic signals exhibit similar properties to random signals, and easily implemented on hardware, some authors have attempted using chaotic signals to construct measurement matrices [16-21]. N. L. Trung, et al. [16] continue on the work in [14] on random filter in CS, and examine the use of chaos filters in CS with filter taps calculated from the Logistic map. Numerical simulations indicate that chaos filter generated by Logistic map outperform random filters. L. Yu, et al. [18] construct the measurement matrix with chaotic sequence from Logistic map, and prove that chaotic matrix satisfies RIP with overwhelming probability and has similar performance to the Gaussian random matrix and sparse random matrix. In the subsequent work [19], they demonstrate that Toeplitz-structured chaotic sensing matrix is sufficient to satisfy RIP with high probability. This sensing matrix can be easily built as a filter with a small number of taps. M. Frunzete, et al. [20] generate the measurement matrix by using the Tent map and show that for any initial condition or parameter the performances of the matrix are similar. The matrices constructed by other chaotic dynamical systems [17,21], such as Chua, Lorenz, Chen, Liu, Lu, and so on, also have been shown to have similar performance to random Gaussian, Bernoulli and uniformly distributed sequences. But all these chaotic sequences in CS mentioned in the literatures are produced by computer simulation, not by the real hardware.

In this paper, we proposed that a new chaotic sequence generated by Colpitts oscillator can also be effectively used to construct the measurement matrix in CS for super-resolution image reconstruction of image sensors and the Colpitts chaotic signal is taken from the actual circuit.

The paper is organized as below. A brief of overview of compressive sensing is given in section II. The descriptions of Colpitts oscillator and Colpitts chaotic sensing matrix are presented in Section III. Numerical simulations of one dimensional time-sparse signal and two dimensional Wavelet-sparse image in CS with Colpitts chaotic sensing matrix are presented and the performance comparison between chaos-based sensing matrix and random matrix is given in Section IV. In Section V we draw some conclusions from the results of our simulation study.

II. COMPRESSIVE SENSING THEORY

Consider an N-pixel grayscale image as the vector $\mathbf{x} \in \mathbb{R}^{N}$ ($N = n \times n$) which is made by column concatenation of the image and assume that **x** is very sparse or highly compressible in some basis $\mathbf{\Psi}$ (i.e. Fourier, Wavelet, Discrete-Cosine, Hadamard and contourlet basis), then the signal can be represented as $\mathbf{x}=\mathbf{\Psi}\mathbf{s}$ (**s** is K-sparse, meaning it has K significant components, $K \ll N$). In CS framework, the image is encoded into a relatively small number of incoherent linear measurements by the measurement (sensing) matrix $\mathbf{\Phi} \in \mathbb{R}^{M \times N}$. The obtained measurement vector

$\mathbf{y} \in \mathbb{R}^{M} (M < N)$ can be expressed as a linear projection

$$\mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi \Psi s} = \mathbf{\Theta s} \qquad (1)$$

Given **y**, **Φ** and **Ψ,** the objective is then to faithfully recover **s** (and hence **x**) from **y** with as small *M* as possible. In order to successfully reconstruct an image with incomplete measurements, the sensing matrix must satisfy the RIP property, which is expressed as follows:

$$(1-\delta_K)\|\mathbf{v}\|_2^2 \le \|\mathbf{\Theta v}\|_2^2 \le (1+\delta_K)\|\mathbf{v}\|_2^2 \qquad (2)$$

where $\delta_K \in (0,1)$ for all *K*-sparse vectors **v**. When this property holds, all *K*-subsets of the columns of $\mathbf{\Theta}$ are nearly orthogonal, or else, a *K*-sparse signal may be in the null space of $\mathbf{\Theta}$ and thus impossible to reconstruct these vectors. It has been shown that **Φ** and **Ψ** which are incoherent will satisfy RIP.

From (2), we can see that δ_K is determined by $\mathbf{\Theta}$ and *K*. Apparently, *K* depends on the signal and its sparse representation matrix **Ψ**. Thus, what we can design is only the sensing matrix **Φ**. The goal of the design or optimization is making δ_K as minimal as possible. In fact, RIP is a sufficient but not necessary condition. Meanwhile, there is no fast algorithm to verify whether a given matrix meets the RIP. A more practical criterion to choose the sensing matrix is to minimize the coherence, which measures the largest correlation between any two elements of **Φ** and **Ψ.** If **Φ and Ψ** contain correlated elements, the coherence is large. Otherwise, it is small. Mathematically, coherence is defined as:

$$\mu\langle\mathbf{\Phi},\mathbf{\Psi}\rangle = \sqrt{N}\max_{1\le i,j\le N}\left|\left\langle\mathbf{\Phi}_i^T,\mathbf{\Psi}_j\right\rangle\right| \qquad (3)$$

where $\mathbf{\Phi}_i$ are rows of **Φ** and $\mathbf{\Psi}_j$ are columns of **Ψ**, respectively. The value of coherence is between 1 and $\sqrt{N}$.

If **Φ** is incoherent with **Ψ**, **s** can be recovered from **y** by solving the following l_1-optimization problem:

$$\min\|\mathbf{s}\|_1 \quad subject\ to \quad \mathbf{y} = \mathbf{\Phi\Psi s} \qquad (4)$$

There are various sparse approximation algorithms, such as l_1-optimization based Basic Pursuit (BP), Orthogonal Matching Pursuit (OMP), Gradient Projection for Sparse Reconstruction (GPRS) and so on. Since this paper does not focus on the reconstruction algorithms, we just briefly use the OMP algorithm to reconstruct the original signal. OMP is widely adopted in CS for its high speed and its ease of implementation.

III. CHAOTIC SENSING MATRIX

Finding a proper sensing matrix satisfying RIP is one of the most important problems in CS. Chaotic sequence has been proposed to construct the sensing matrix in [18]. Since pseudo-random numbers can be obtained by computing a chaotic system, we can use a chaotic system to generate a pseudo-random matrix in deterministic approach and hence satisfies RIP similar to Gaussian or Bernoulli matrix. Moreover, chaotic system is easy to be implemented in physical electric circuit and only one initial state is necessary to memorized. In this paper, we just use chaotic sequence sampled from Colpitts oscillator circuit, to construct Toeplitz-structured sensing matrix, which has been proved to be sufficient to retain RIP property with overwhelming probability [19]. The use of Toeplitz matrix in CS application has the following advantages: the required independent chaotic variables are small, only $O(n)$; and the multiplication can be efficiently implemented using FFT.

Colpitts oscillator is one of the well-known electronic oscillators for generating chaotic signal under some special sets of its parameters. The classical configuration of the Colpitts oscillator contains a bipolar junction transistor (BJT) as the gain element and a resonant tank consisting of an inductor L and a pair of capacitors C_1 and C_2, as illustrated in figure 1. Note that the bias is provided by the current source I_0.

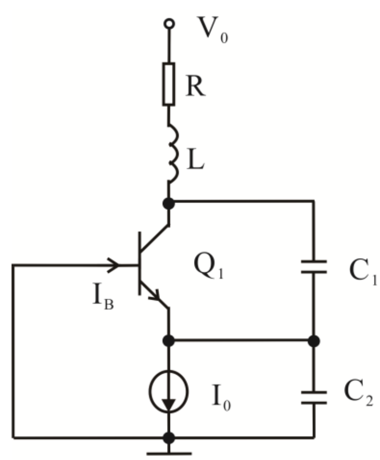

Figure 1. Schematic of the Colpitts oscillator

The current flowing through the inductor L and the voltage across capacitor C_i (i=1,2) are denoted by I_L and V_{Ci}, respectively. According to the Kirchhoff's electric circuit laws, the state equations for the schematic in figure 1 are the following:

$$\begin{cases} C_1 \dfrac{dV_{C_1}}{dt} = -f\left(V_{C_2}\right) + I_L \\ C_2 \dfrac{dV_{C_2}}{dt} = I_L - I_0 \\ L \dfrac{dI_L}{dt} = -V_{C_1} - V_{C_2} - RI_L + V_{CC} \end{cases} \quad (5)$$

where $f(\bullet)$ is the driving-point characteristic of the nonlinear resistor. By introducing a set of dimensionless state variables (x_1, x_2, x_3), the normalized state equations of the Colpitts oscillator can be written in the form:

$$\begin{cases} \dot{x} = \dfrac{g}{Q(1-k)}\left[-n(y) + z\right] \\ \dot{y} = \dfrac{g}{Qk} z \\ \dot{z} = -\dfrac{Qk(1-k)}{g}\left[x + y\right] - \dfrac{1}{Q} z \end{cases} \quad (6)$$

where $n(y) = \exp(-y) - 1$, $k = C_2/(C_1 + C_2)$, $Q = (\omega_0 L / R)$ represents the quality factor of the unloaded tank circuit , $\omega_0 = \sqrt{(C_1 + C_2)/(LC_1C_2)}$ is the resonant frequency of the unloaded *L*-*C* tank circuit, and *g* is loop gain of the oscillator.

The hardware implementation of Colpitts oscillator and the corresponding prototype board is shown in figure 2, respectively. In the circuit, C_3 = 2 pF, $C_4 = C_0$ = 100 nF, R_1 = 5.1 kΩ, R_2 = 3 kΩ, R_3 = 200 Ω, L_0 = 10 μH and two BFG520XR transistors (Q1 and Q2) are adopted. The parameters of tank elements are L = 15 nH, $C_1 = C_2$ = 10 pF, R_e = 100 Ω, R = 10 Ω. The supply voltages V_1 and V_2, are adjusted to obtain chaotic performance. When V_1=1.8 V, V_2=10.1 V, Colpitts circuit exhibits chaotic behavior. The chaotic signal output is detected and saved by a digital oscilloscope (LeCroy SDA806Zi-A). Figure 3 shows time series of the signal collected by the oscilloscope and the corresponding phase diagram.

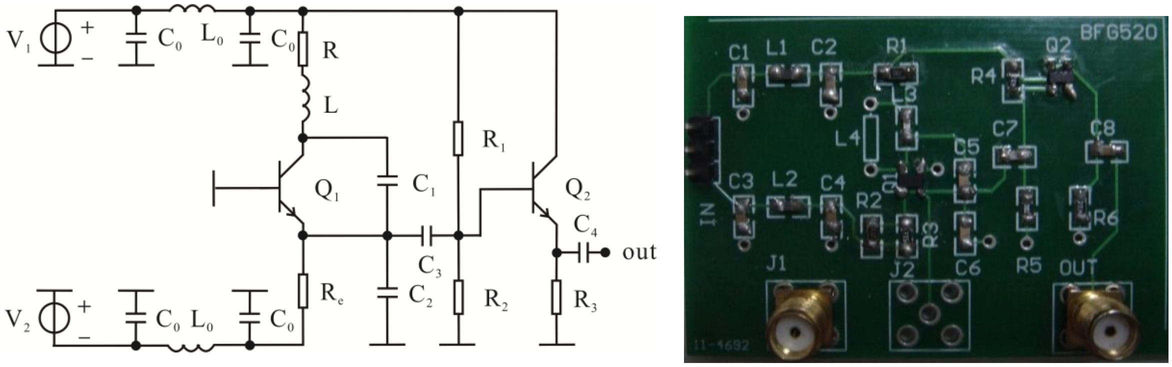

Figure 2. Circuit Diagram (left) and prototype board (right) of Colpitts oscillator

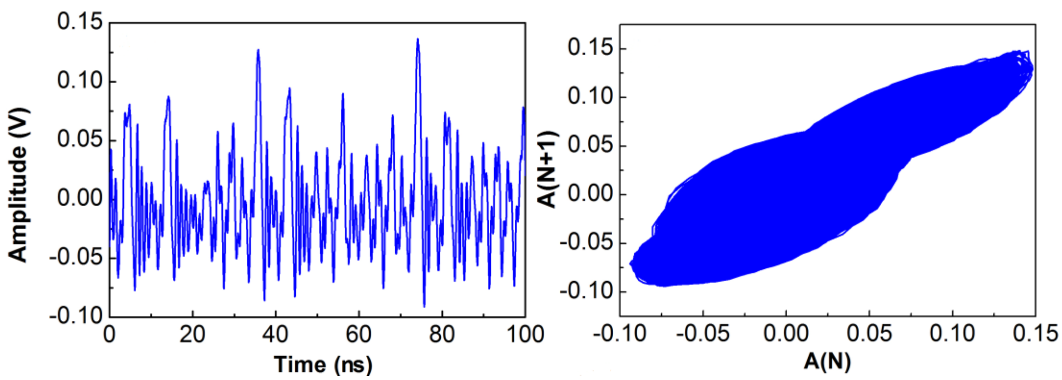

Figure 3. Time series (left) and phase diagram (right) of Colpitts chaotic signal collected by the oscilloscope

Figure 4 presents the normalized autocorrelation of the Colpitts chaotic signal, which is thumbtack-like, and it reveals rapid decorrelation between close samples, thus making this sequence akin to a random trajectory. Figure 5 shows its probability density function.

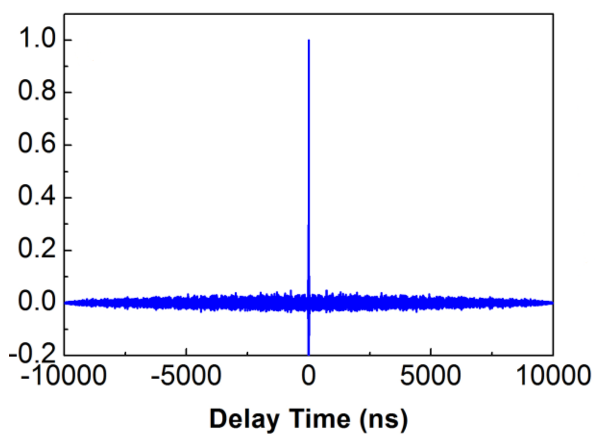

Figure 4. Autocorrelation of the chaotic signal sampled from Colpitts oscillator

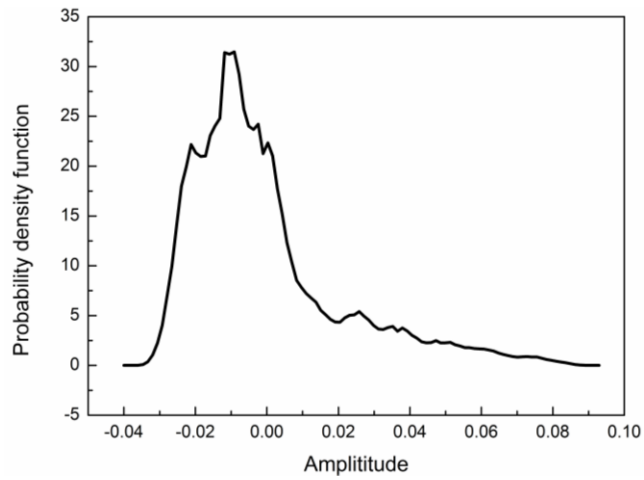

Figure 5. Probability density function of the chaotic signal sampled from Colpitts oscillator

Then, the process of construction of the measurement matrix is as follows:

1) Generate a chaotic sequence $\mathbf{c} = [c_0, c_1, \cdots, c_{N-1}]$ of length $1 \times N$. The chaotic sequences are sampled from the output signal of Colpitts oscillator circuit and the sample interval can be selected arbitrarily because its autocorrelation is thumbtack-like. Here, we select unit sample interval.
2) Construct a Toeplitz-structured matrix of size $M \times N$ as follows:

$$\mathbf{\Phi} = \sqrt{\frac{8}{M}} \begin{bmatrix} c_{N-1} & c_{N-2} & \cdots & c_0 \\ c_0 & c_{N-1} & \cdots & c_1 \\ \vdots & \vdots & \vdots & \vdots \\ c_{M-2} & c_{M-3} & \cdots & c_{M-1} \end{bmatrix} \tag{7}$$

where $\sqrt{8/M}$ is for normalization. L. Yu, et al [19] proved that for Toeplitz-structured chaotic sensing matrix, if $M \geq c_1 K^3 \ln(N/K)$, the RIP of order *K* with constant δ_K is verified with probability at least $1 - \exp(-c_2 t / M^2)$.

IV. NUMERICAL SIMULATION

We provide some numerical examples to verify that Colpitts chaotic sequence is a powerful approach to compressive signal acquisition and reconstruction, and the performance of it can be comparable to that of random Gaussian distributed sequence and other existing chaotic sequences.

Consider a discrete time-sparse signal **x** with N=512 samples and K=10 spikes, as shown in figure 8(a), is being reconstruction from M=80 measurements vectors. This is, of course, a highly under-determined problem. Here, we compare the reconstruction performance of Colpitts chaotic sensing matrix with that of other random or chaotic sensing matrix, such as Gaussian, partial Hadamard, Logistic, and Tent. Figure 6 shows the corresponding random or chaotic sequences, all normalized to have zero mean and unity variance. The obtained measurements, generated from random or chaotic sensing matrix, are shown in figure 7. It can be seen that the original signal $\mathbf{x} \in \mathbb{R}^N$ has been randomly projected on the measurements $\mathbf{y} \in \mathbb{R}^M$. The reconstructed signals using OMP are shown in figure 8. Clearly, when N=512, M=80, K=10, we can obtain exact reconstruction using chaotic sequences or Gaussian sequence. For fixed N and K, when M decreases, the signal may be impossible to exact recovery. Figure 9 illustrates an example of unsuccessful reconstruction for M=55. Note that it is obtained from one simulation run, so we cannot conclude that the performance of Gaussian matrix is better, and we will compare those matrices later.

To further verify the performance of Colpitts chaotic sequence, we use the error rate, that is, the probability of incorrect reconstruction as a criterion, which is expressed as follows:

$$\mathbf{Pr}\left\{e = \left\|x - \hat{x}\right\| / \left\|x\right\| > \varepsilon = 0.01\right\} \qquad (8)$$

where $\hat{x}$ is the reconstructed vector and $\|\cdot\|$ is the l_2 norm.

Figure 10 depicts the error rate curve as a function of the measurement number M for different sparsity K. It can be found that there is a minimum measurement number for perfect reconstruction and the value increases as the sparsity K increases. Meanwhile, the error rate rises with the increase of K for fixed measurement number and the error rate maintains one value firstly, drops rapidly in the middle section, and then holds zero with increasing M for fixed sparsity. From figure 10, we can also see that for K=10, M=80, the error rate is nearly zero, and when M=55, the error rate is approximately 0.3, which is consistent with the result of the above example.

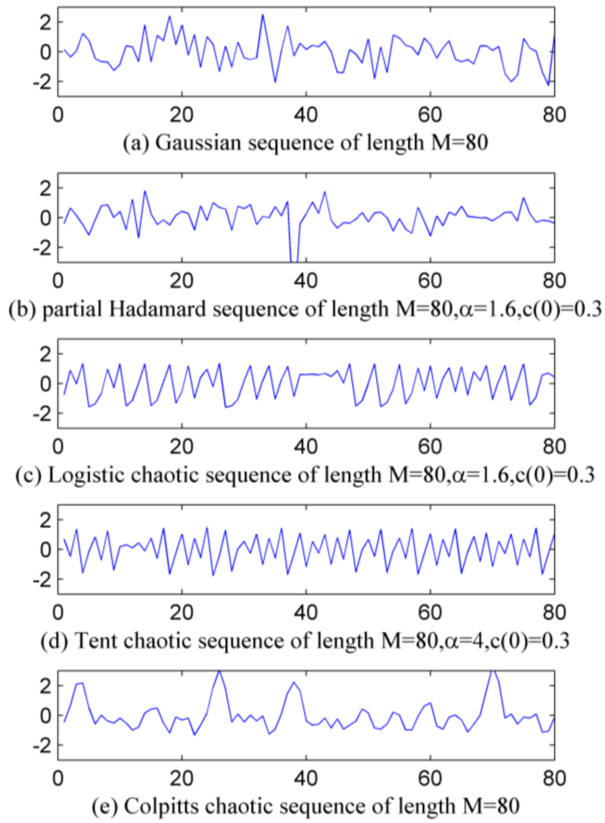

Figure 6. Random and chaotic sequences

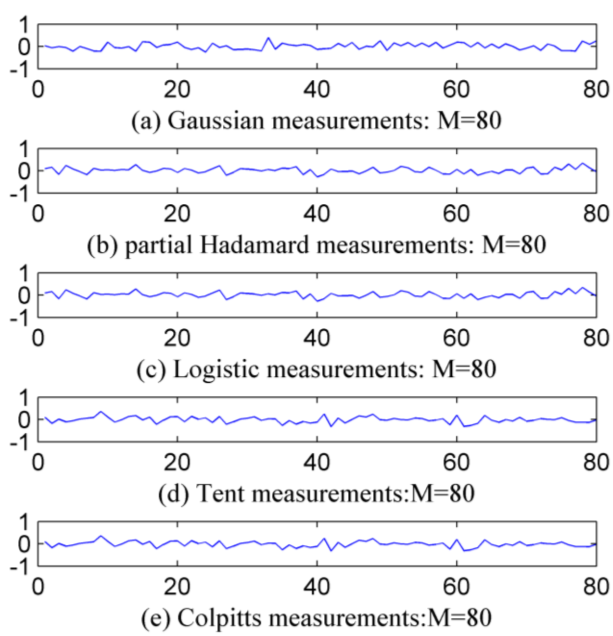

Figure 7. The measurements of the signal

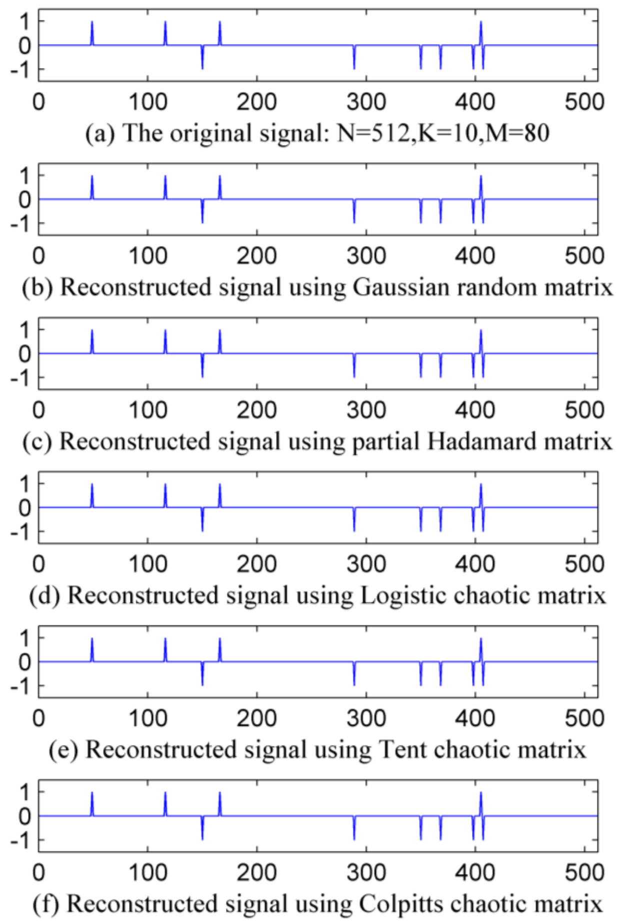

Figure 8. Illustrative example showing successful reconstruction using Gaussian and chaotic sensing matrix, N=512,M=80,K=10

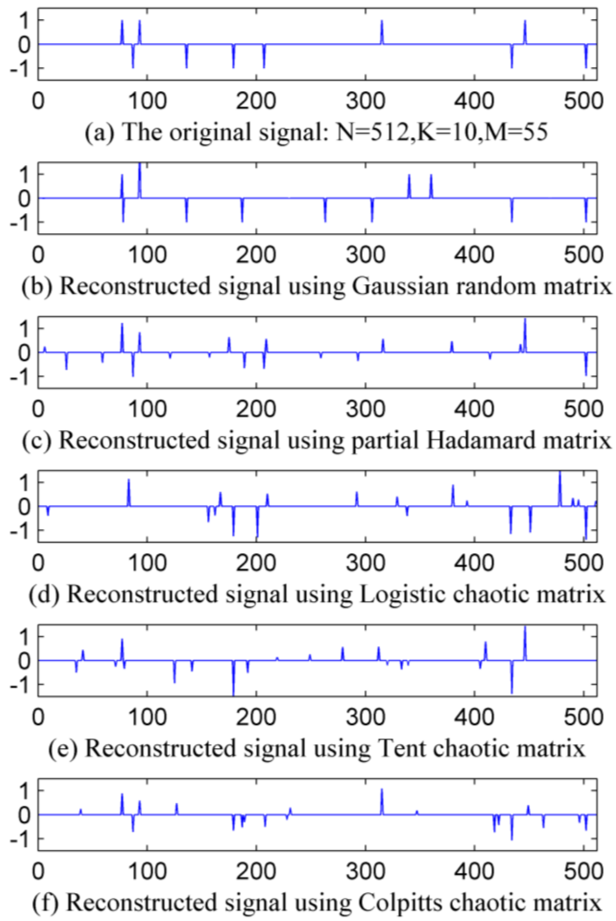

Figure 9. Illustrative example showing unsuccessful reconstruction, N=512,M=55,K=10

Figure 11 shows the error rate curves of different random or chaotic sensing matrix for fixed N=512 and M=80, and for various K, obtained from 100 simulation runs. Apparently, the performance of Gaussian random sensing matrix and Logic chaotic sensing matrix is similar, which is in accord with the result in [18]; while the error rate of Colpitts chaotic sensing matrix is slightly smaller than that of other sensing matrices, that is to say, our proposed Colpitts chaotic sensing matrix has better performance in CS.

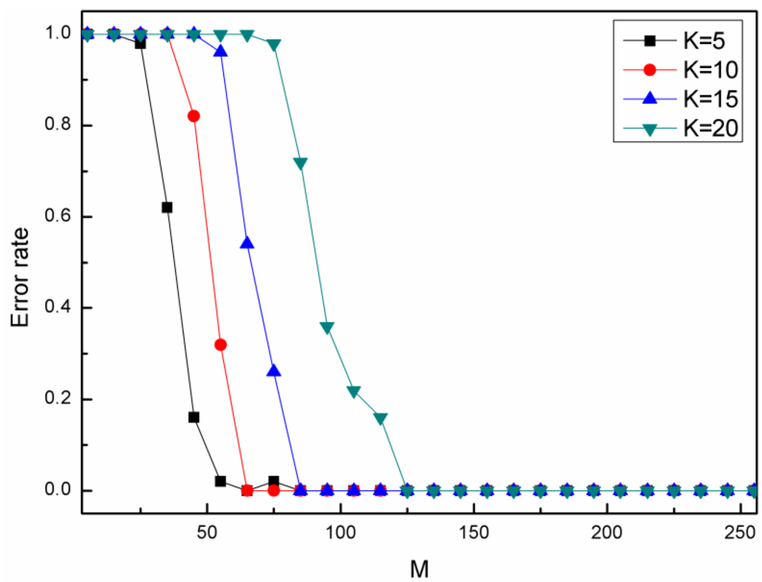

Figure 10. Error rate as a function of the measurement number M for different signal sparsity, N=512

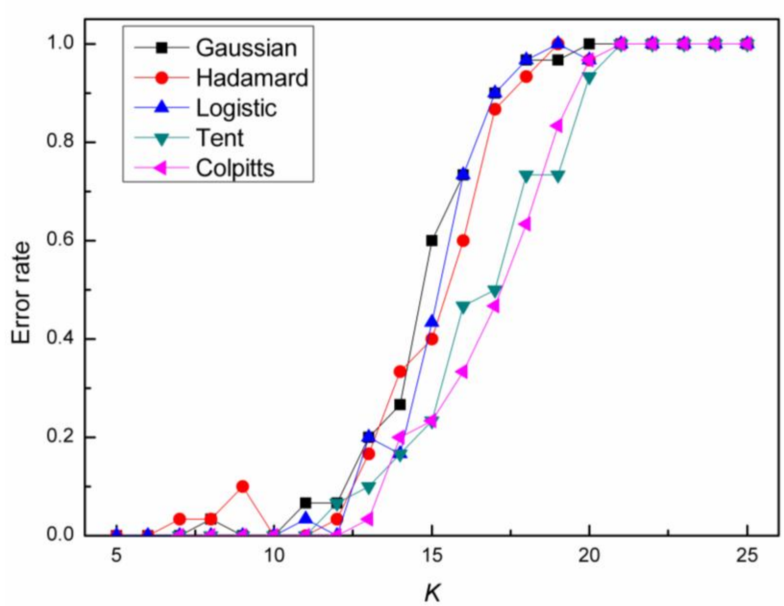

Figure 11. Error rate as a function of the signal sparsity K for N=512, M=80

Since correct recovery of **x** does not depend on the measurement matrix, and is solely determined by N and M, we give the dependence of the maximum sparisity K_{max} on the ratio N/M for $\varepsilon = 0.01$ and fixed signal size N=512, as shown in figure 12. K_{max} is determined as the maximum sparsity for which error rate is smaller than 0.1. It can be found that the maximum sparsity in the case of chaotic matrix is similar to that in the case of Gaussian random matrix, that is, the maximum sparsity decreases as N/M increases, in more detail, $K_{\max}$ decreases roughly by factor 2 if N/M (below 4) is doubled, while decline slowly for N/M more than 4.

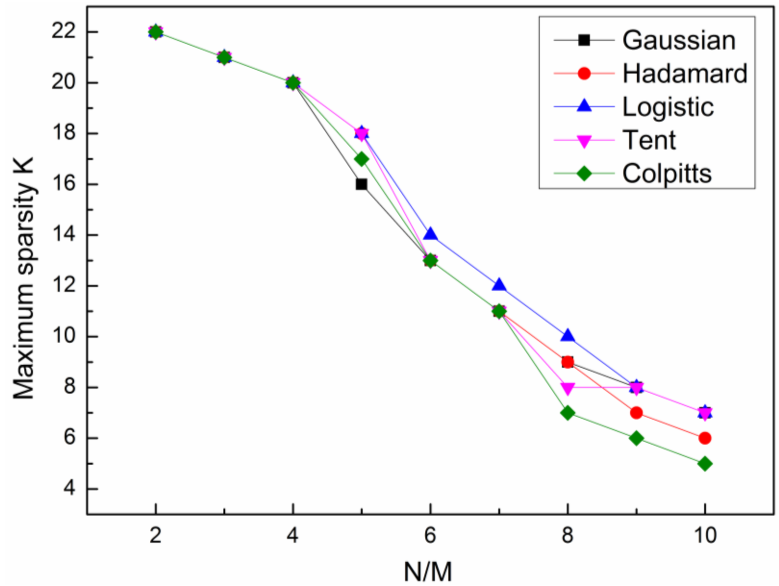

Figure 12. Dependence of maximum sparsity on N/M for fixed signal size N=512

We also give an example of two-dimensional image reconstruction by Colpitts chaotic sensing matrix (CCM). Consider a monochrome “Lena” image with size 256×256 (shown in figure 13), we measure this image with sample rate at 0.3,0.5, 0.7 and 0.9 respectively, then use OMP algorithm to reconstruct the original images. We use Haar wavelet for our compression basis. The Peak Signal to Noise Ratio (PSNR) is used as a criterion for the reconstruction performance.

$$PSNR = 10\,\mathbf{lg}\frac{\left(2^{n}-1\right)^{2}\times M\times N}{\left\|x-\hat{x}\right\|^{2}} \qquad (9)$$

where $M\times N$ is the image size and n means the bit value per sample of the pixel (usually, n=8). The higher value of PSNR, the better accuracy rate of reconstruction.

The results are listed in figure 14 and the corresponding PSNR values are given. Clearly, the more the samples or measurements are used, the better the performance of reconstruction is obtained. But even if the samples are fewer, the outline of the image can be get due to CS theory.

To further prove the efficiency of CCM, we compare the reconstruction performance of CCM with that of Gaussian random matrix, partial Hadamard matrix, Logistic chaotic matrix, Tent chaotic matrix. Figure 15 presents the reconstructed images using different sensing matrices with sample rate at 0.5 and the corresponding PSNR values are also listed. From visual observations and the values of PSNR, it can be concluded that the performance of those random or chaotic sensing matrices are similar, and the proposed CCM has slightly better result than others, from observing the nose and the lip of the woman. We also perform extensive simulations with those sensing matrices under other sample rate. Figure 16 illustrates the PSNR curve as a function of sample rate for different sensing matrices. It can be seen that the performance of CCM is comparable to that of other sensing matrices, which is consistent with the results in the first example. Therefore, compressive sensing with Colpitts chaotic circuit can be applied for super-resolution image reconstruction of image sensors.

Figure 13. The original image with size 256×256

Figure 14. Reconstruction of CS using CCM under different sample rate: 0.3,0.5,0.7,0.9 and the corresponding PSNR values are 20.148,25.369,29.579 and 33.021

(a) Gaussian, PSNR=25.257 (b) Hadamard, PSNR=25.221 (c) Logistic, PSNR=25.161

(d) Tent, PSNR=25.276 (e) Colpitts, PSNR=25.369

Figure 15. Reconstruction of CS using different sensing matrices with 0.5 sample rate

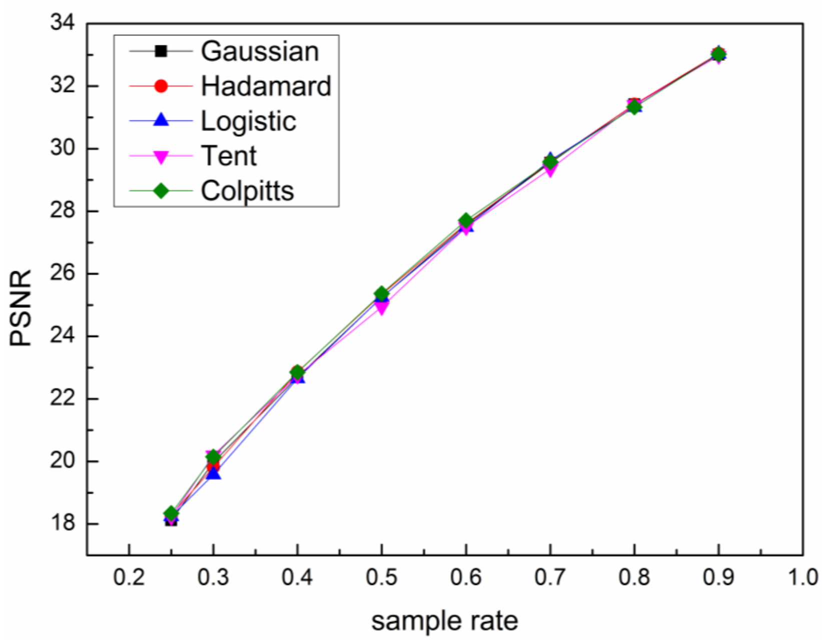

Figure 16. The PSNR curves as a function of sample rate for different sensing matrices

VI. CONCLUSIONS

In this paper, we demonstrate the use of Colpitts chaotic signal to construct measurement matrix in compressive sensing. From numerical simulations, it shows that Colpitts chaotic matrix has similar performance to existing random matrix and other chaotic matrices. Rather than using the simulated random or chaotic sequences, here we use the real sampled data from Colpitts chaotic oscillator circuit to generate the sensing matrix, so the result is more beneficial to designing practical CS-based imaging sensors. Meanwhile, Toeplitz-structured Colpitts sensing matrix can be implemented theoretically in an low cost integrated circuit board containing a CMOS dynamic shift register and Colpitts chaotic circuit, which is our next work.

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REFERENCES

[1]Z. Y. Xiong, X. P. Fan, S. Q. Liu, Y. Z. Li, and H. Zhang, "Performance analysis for dct-based coded image communication in wireless multimedia sensor networks", International Journal on Smart Sensing and Intelligent Systems, Vol. 6, No. 1, 2013, pp. 120-135.

[2]B. Wu, Y. P. Feng, and H. Y. Zheng. "Posterior belief clustering algorithm for energy-efficient tracking in wireless sensor networks", International Journal on Smart Sensing and Intelligent Systems, Vol. 7, No. 3, 2014, pp. 925-941.

[3] L. K. Lai, T. S. Liu, "Design of auto-focusing modules in cell phone cameras", International Journal on Smart Sensing and Intelligent Systems, Vol. 4, No. 4, 2011, pp. 568-582.

[4] E. Candès, J. Romberg and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information", IEEE Transactions on Information Theory, Vol. 52, No. 2, 2006, pp. 489-509.

[5] E. Candès and T. Tao, "Near optimal signal recovery from random projections: Universal encoding strategies", IEEE Transactions on Information Theory, Vol. 52, No. 12, 2006, pp. 5406-5425.

[6] D. Donoho, "Compressed sensing", IEEE Transactions on Information Theory, Vol. 52, No. 4, 2006, pp. 1289-1306.

[7] M. F. Duarte, M. A. Davenport, D. Takhar, J. N. Laska, T. Sun, K. F. Kelly and R. G. Baraniuk, "Single pixel imaging via compressive sampling", IEEE Signal Processing Magazine, Vol. 25, No. 2, 2008, pp. 83-91.

[8] Y Wu, P Ye, I. O. Mirza, G. R. Arce and D. W. Prather, "Experimental demonstration of an optical-sectioning compressive sensing microscope(CSM)", Optics Express, Vol. 18, No. 24, 2010, pp. 24565-24578.

[9] R. Baraniuk and P. Steeghs, "Compressive radar imaging", IEEE Radar Conference, pp. 128-133, Boston, MA, 17-20 April 2007.

[10] M. Zhang and A. bermak, "Compressive acquisition CMOS image sensor—From algorithmic solution to hardware implementation", IEEE Transactions on Very Large Scale Integration Systems, Vol. 10, No.3, 2010, pp. 490-500.

[11] M. R. Dadkhah, M. J. Deen and S. Shirani, "Block-based compressive sensing in a CMOS image sensor", IEEE Sensors Journal, Vol. 14, No. 8, 2012, pp. 2897-2909.

[12] R . F. Marcia and R. M. Willett, “Compressive coded aperture superresolution image reconstruction”, *Proc. of ICASSP*, pp. 833-836, Las Vegas, NV, March 31-April 4 2008.

[13] J. Haupt and R. Nowak, “Signal reconstruction from noisy random projections”, IEEE Transactions on Information Theory, Vol. 52, No. 9, 2006, pp. 4036-4048.

[14] J. A. Tropp, W. B. Wakin, M. F. Duarte, D. Baron and R. G. Baraniuk, “Random filters for compressive sampling and reconstruction”, *Proc. of ICASSP*, pp. 872-875, Toulouse, France, 14-19 May 2006,

[15] J. Romberg, “Compressive sensing by random convolution”, SIAM Journal on Imaging Sciences, Vol. 2, No. 4, 2009, pp. 1098-1128.

[16] N. L. Trung, D. V. Phong, Z. M. Hussain, H. T. Huynh, V. L. Morgan and J. C. Gore, “Compressed sensing using chaos filters”, *Proc. of ATNAC*, pp. 219–223, Adelaide, SA, 7-10 December 2008.

[17] V. Kafedziski and T. Stojanovski. “Compressive sampling with chaotic dynamical systems“. *Proc. of 19th TELFOR*, pp. 695-989, Belgrade, Yugoslavia, 22-24 November 2011.

[18] L. Yu, J. P. Barbot, G. Zheng and H. Sun, “Compressive sensing with chaotic sequence”, IEEE Signal Processing Letters, Vol. 17, No. 8, 2010, pp. 731–734.

[19] L. Yu, J. P. Barbot, G. Zheng and H. Sun, “Toeplitz-structured chaotic sensing matrix for compressive sensing”, *Proc. of CSNDSP*, pp. 229-233, Newcastle upon Tyne, 21-23 July 2010.

[20] G. Sengupta, T.A.Win, C. Messom, S. Demidenko and S.C. Mukhopadhyay, “Defect analysis of grit-blasted or spray printed surface using vision sensing technique”, Proceedings of Image and Vision Computing NZ, Nov. 26-28, 2003, Palmerston North, pp. 18-23.

[21] M. Frunzete, Y. Lei, J. Barbot and A. Vlad, “Compressive sensing matrix designed by tent map, for secure data transmission”, *Proc. of SPA*, pp. 1-6, Poznan, 29-30 September 2011.

[22] G. Chen, Q. Chen, D. Zhang and D. Zhou, “The characteristic of different chaotic sequences for compressive sensing”, *Proc. of 5th CISP*, pp. 1475-1479, Chongqing, China, 16-18 October, 2012.